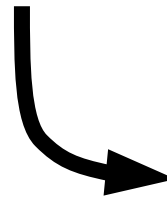
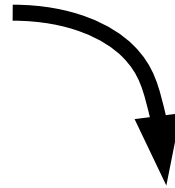




# Machine Learning with Scikit-Learn

Andreas Mueller (NYU Center for Data Science, scikit-learn)

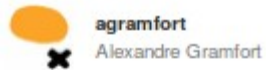
# Me



Classification  
Regression  
Clustering  
Semi-Supervised Learning  
Feature Selection  
Feature Extraction  
Manifold Learning  
Dimensionality Reduction  
Kernel Approximation  
Hyperparameter Optimization  
Evaluation Metrics  
Out-of-core learning

.....





**agramfort**  
Alexandre Gramfort



**AlexanderFabisch**  
Alexander Fabisch



**alextp**  
Alexandre Passos



**amueller**  
Andreas Mueller



**arjoly**  
Arnaud Joly



**bdholt1**  
Brian Holt



**GaelVaroquaux**  
Gael Varoquaux



**glouppe**  
Gilles Louppe



**jakevdp**  
Jake Vanderplas



**jaquesgrobler**  
Jaques Grobler



**jnothman**



**kastnerkyle**  
Kyle Kastner



**bthirion**  
bthirion



**chrisfilo**  
Chris Filo Gorgole...



**cournape**  
David Cournapeau



**duchesnay**  
Duchesnay



**dwf**  
David Warde-Farley



**fabianp**  
Fabian Pedregosa



**kuantkid**  
Wei Li



**larsmans**  
Lars



**lucidfrontier45**  
Shiqiao Du



**mblondel**  
Mathieu Blondel



**MechCoder**  
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**ndawe**  
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**NelleV**  
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**ogrisel**  
Olivier Grisel



**paolo-losi**  
Paolo Losi



**pprett**  
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**robertlayton**  
Robert Layton



**ronw**  
Ron Weiss



**satra**  
Satrajit Ghosh



**sklearn-ci**



**vene**  
Vlad Niculae



**VirgileFritsch**  
Virgile Fritsch



**vmichel**  
Vincent Michel



**yarikoptic**  
Yaroslav Halchenko



## Documentation of scikit-learn 0.17

### Quick Start

A very short introduction into machine learning problems and how to solve them using scikit-learn. Introduced basic concepts and conventions.

### User Guide

The main documentation. This contains an in-depth description of all algorithms and how to apply them.

### Other Versions

- [scikit-learn 0.18 \(development\)](#)
- [scikit-learn 0.17 \(stable\)](#)
- [scikit-learn 0.16](#)
- [scikit-learn 0.15](#)

### Tutorials

Useful tutorials for developing a feel for some of scikit-learn's applications in the machine learning field.

### API

The exact API of all functions and classes, as given by the docstrings. The API documents expected types and allowed features for all functions, and all parameters available for the algorithms.

### Additional Resources

Talks given, slide-sets and other information relevant to scikit-learn.

### Contributing

Information on how to contribute. This also contains useful information for advanced users, for example how to build their own estimators.

### Flow Chart

A graphical overview of basic areas of machine learning, and guidance which kind of algorithms to use in a given situation.

### FAQ

Frequently asked questions about the project and contributing.

<http://scikit-learn.org/>

# Doing Machine Learning With Scikit-Learn

# Representing Data

$$X = \begin{pmatrix} 1.1 & 2.2 & 3.4 & 5.6 & 1.0 \\ 6.7 & 0.5 & 0.4 & 2.6 & 1.6 \\ 2.4 & 9.3 & 7.3 & 6.4 & 2.8 \\ 1.5 & 0.0 & 4.3 & 8.3 & 3.4 \\ 0.5 & 3.5 & 8.1 & 3.6 & 4.6 \\ 5.1 & 9.7 & 3.5 & 7.9 & 5.1 \\ 3.7 & 7.8 & 2.6 & 3.2 & 6.3 \end{pmatrix}$$

# Representing Data

one sample

$$X = \begin{pmatrix} 1.1 & 2.2 & 3.4 & 5.6 & 1.0 \\ 6.7 & 0.5 & 0.4 & 2.6 & 1.6 \\ 2.4 & 9.3 & 7.3 & 6.4 & 2.8 \\ 1.5 & 0.0 & 4.3 & 8.3 & 3.4 \\ 0.5 & 3.5 & 8.1 & 3.6 & 4.6 \\ 5.1 & 9.7 & 3.5 & 7.9 & 5.1 \\ 3.7 & 7.8 & 2.6 & 3.2 & 6.3 \end{pmatrix}$$



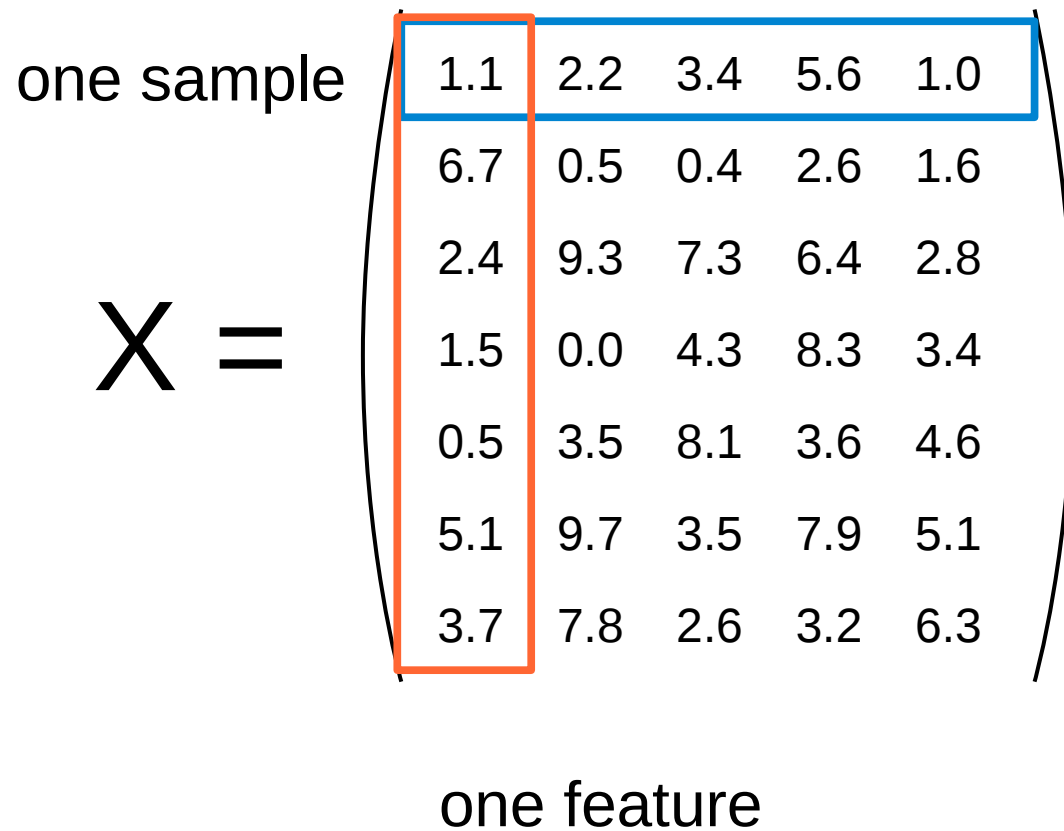
# Representing Data

one sample

$X =$

1.1	2.2	3.4	5.6	1.0
6.7	0.5	0.4	2.6	1.6
2.4	9.3	7.3	6.4	2.8
1.5	0.0	4.3	8.3	3.4
0.5	3.5	8.1	3.6	4.6
5.1	9.7	3.5	7.9	5.1
3.7	7.8	2.6	3.2	6.3

one feature



# Representing Data

one sample

$$X = \begin{pmatrix} 1.1 & 2.2 & 3.4 & 5.6 & 1.0 \\ 6.7 & 0.5 & 0.4 & 2.6 & 1.6 \\ 2.4 & 9.3 & 7.3 & 6.4 & 2.8 \\ 1.5 & 0.0 & 4.3 & 8.3 & 3.4 \\ 0.5 & 3.5 & 8.1 & 3.6 & 4.6 \\ 5.1 & 9.7 & 3.5 & 7.9 & 5.1 \\ 3.7 & 7.8 & 2.6 & 3.2 & 6.3 \end{pmatrix}$$

one feature

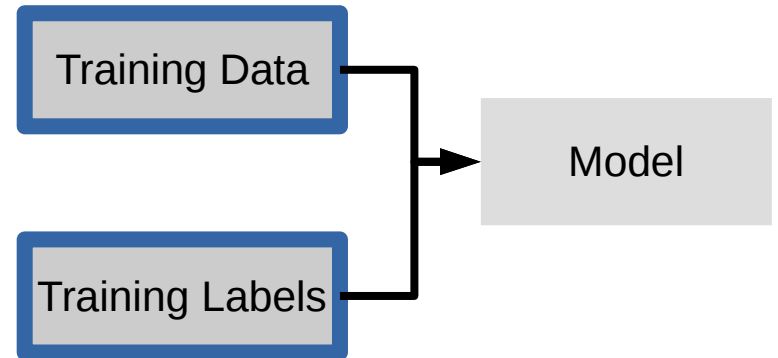
$$y = \begin{pmatrix} 1.6 \\ 2.7 \\ 4.4 \\ 0.5 \\ 0.2 \\ 5.6 \\ 6.7 \end{pmatrix}$$

outputs / labels

# Supervised Machine Learning

```
clf = RandomForestClassifier()
```

```
clf.fit(X_train, y_train)
```

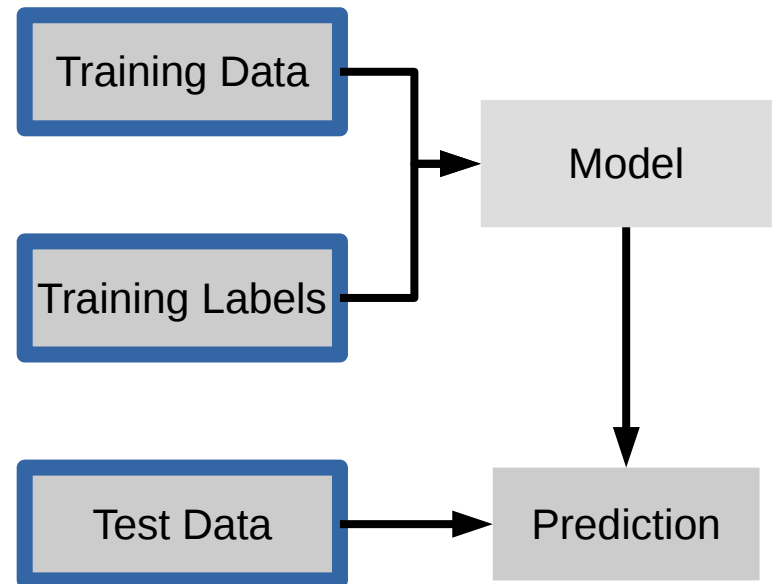


# Supervised Machine Learning

```
clf = RandomForestClassifier()
```

```
clf.fit(X_train, y_train)
```

```
y_pred = clf.predict(X_test)
```



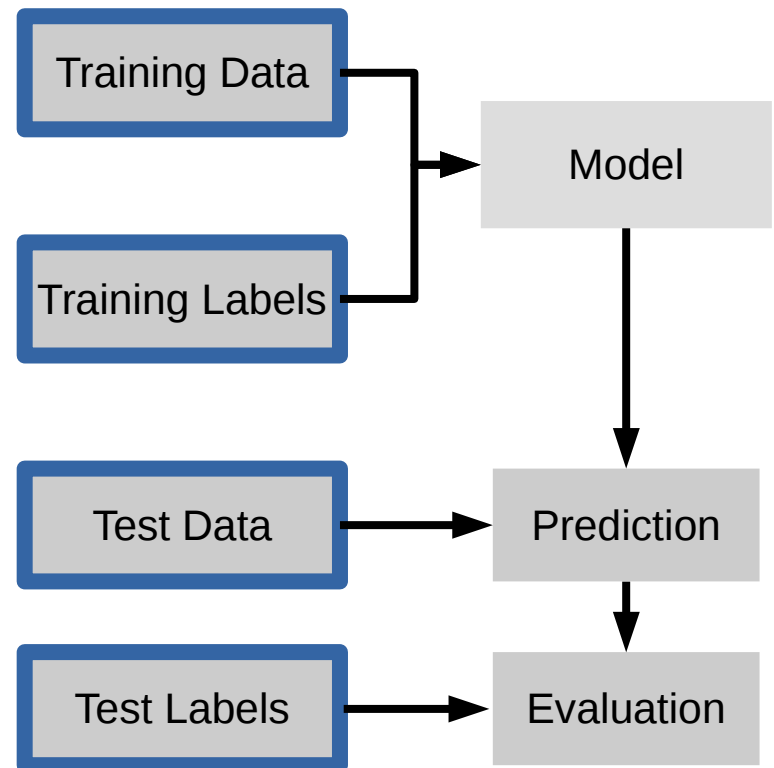
# Supervised Machine Learning

```
clf = RandomForestClassifier()
```

```
clf.fit(X_train, y_train)
```

```
y_pred = clf.predict(X_test)
```

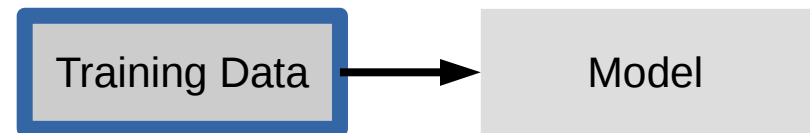
```
clf.score(X_test, y_test)
```



# Unsupervised Transformations

```
pca = PCA()
```

```
pca.fit(X_train)
```

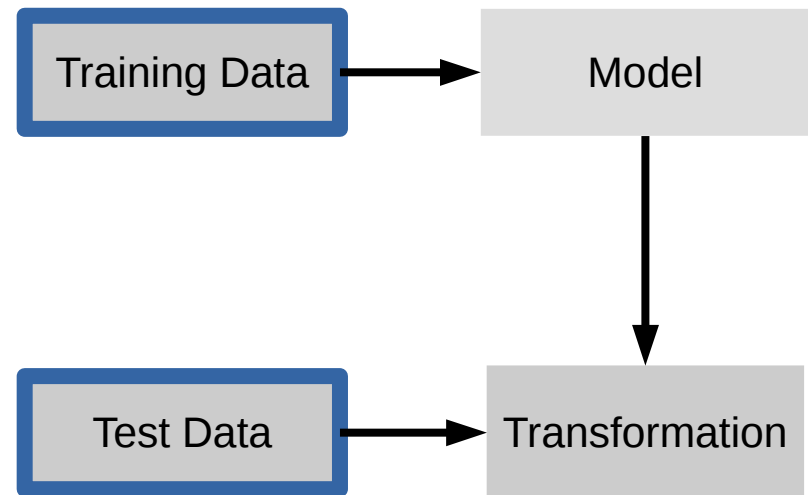


# Unsupervised Transformations

```
pca = PCA()
```

```
pca.fit(X_train)
```

```
X_new = pca.transform(X_test)
```



# Basic API

**`estimator.fit(X, [y])`**

**`estimator.predict`**

**`estimator.transform`**

---

Classification

Preprocessing

Regression

Dimensionality reduction

Clustering

Feature selection

Feature extraction



# Model Evaluation and Model Selection

The diagram illustrates the process of data partitioning. At the top, a single light gray bar represents the entire dataset, labeled 'All Data'. Below this bar, the dataset is divided into two separate horizontal bars. The left bar is light green and labeled 'Training data', while the right bar is light blue and labeled 'Test data'. This visualizes how a single dataset is split into two distinct subsets for model training and evaluation.

All Data

Training data

Test data

All Data

Training data

Test data

Fold 1

Fold 2

Fold 3

Fold 4

Fold 5

All Data

Training data      Test data

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

Split 1

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

All Data

Training data      Test data

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

Split 1

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

Split 2

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

All Data

Training data      Test data

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

Split 1

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

Split 2

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

Split 3

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

Split 4

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

Split 5

Fold 1      Fold 2      Fold 3      Fold 4      Fold 5

# Cross-Validation

```
from sklearn.cross_validation import cross_val_score  
  
scores = cross_val_score(SVC(), X, y, cv=5)  
print(scores)  
  
>> [ 0.92  1.    1.    1.    1. ]
```

All Data

Training data

Test data



All Data

Training data      Test data

Fold 1   Fold 2   Fold 3   Fold 4   Fold 5

Split 1

Fold 1   Fold 2   Fold 3   Fold 4   Fold 5

Split 2

Fold 1   Fold 2   Fold 3   Fold 4   Fold 5

Split 3

Fold 1   Fold 2   Fold 3   Fold 4   Fold 5

Split 4

Fold 1   Fold 2   Fold 3   Fold 4   Fold 5

Split 5

Fold 1   Fold 2   Fold 3   Fold 4   Fold 5

Test data

All Data

Training data      Test data

Fold 1   Fold 2   Fold 3   Fold 4   Fold 5

Split 1	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Split 2	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Split 3	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Split 4	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Split 5	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5

Finding Parameters

Final evaluation

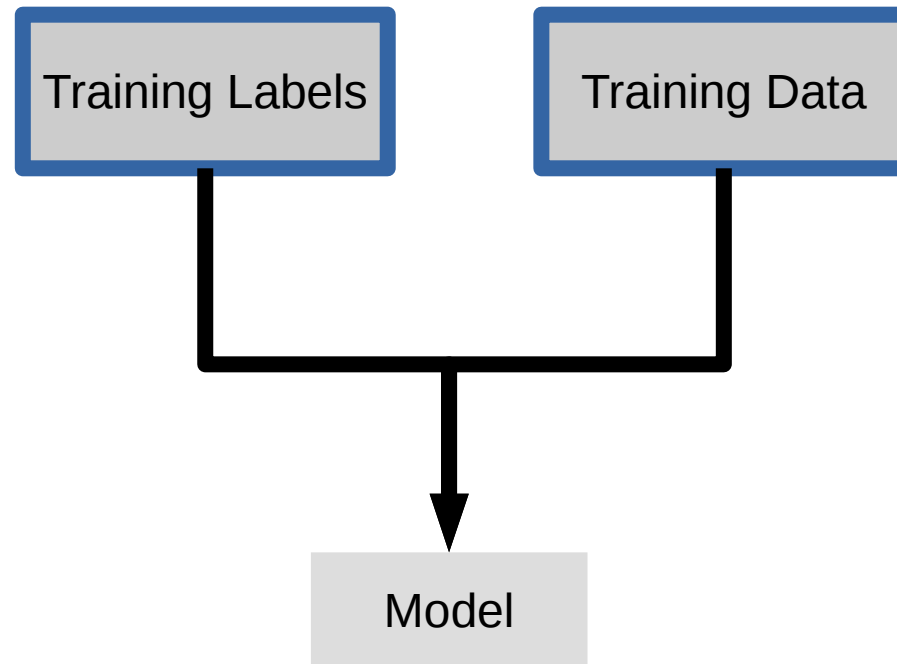
Test data

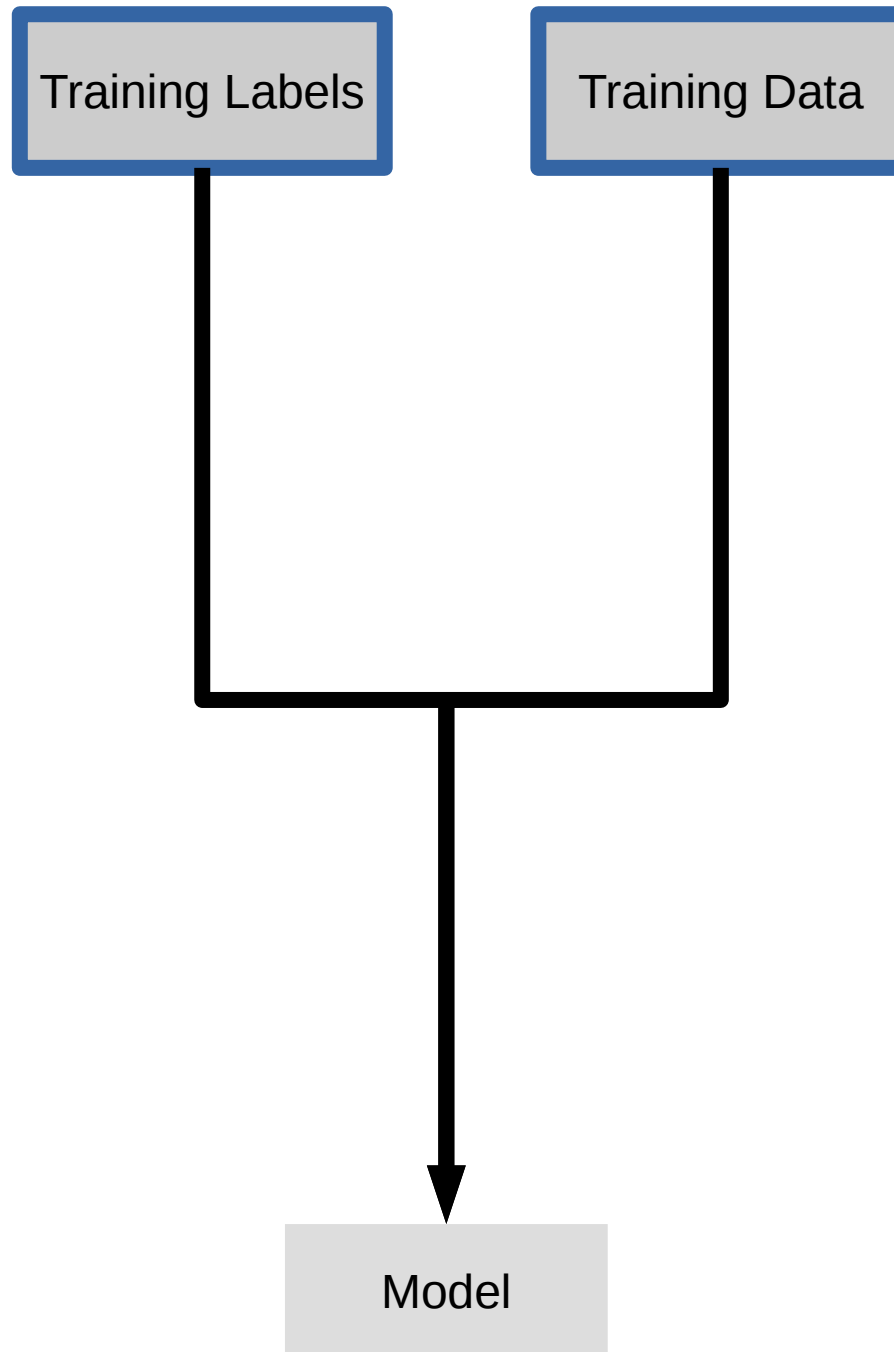
# Cross -Validated Grid Search

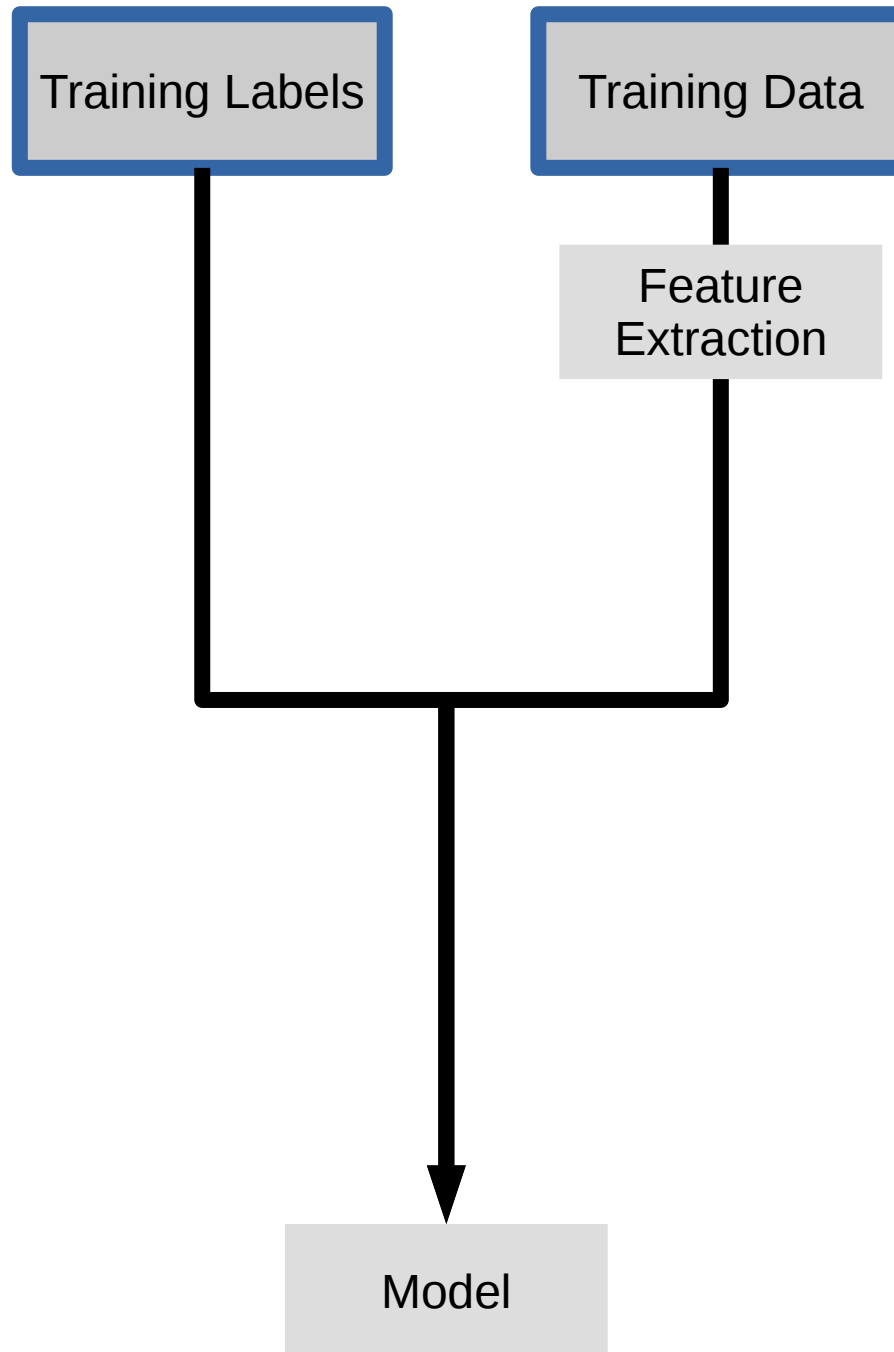
```
from sklearn.grid_search import GridSearchCV
from sklearn.cross_validation import train_test_split

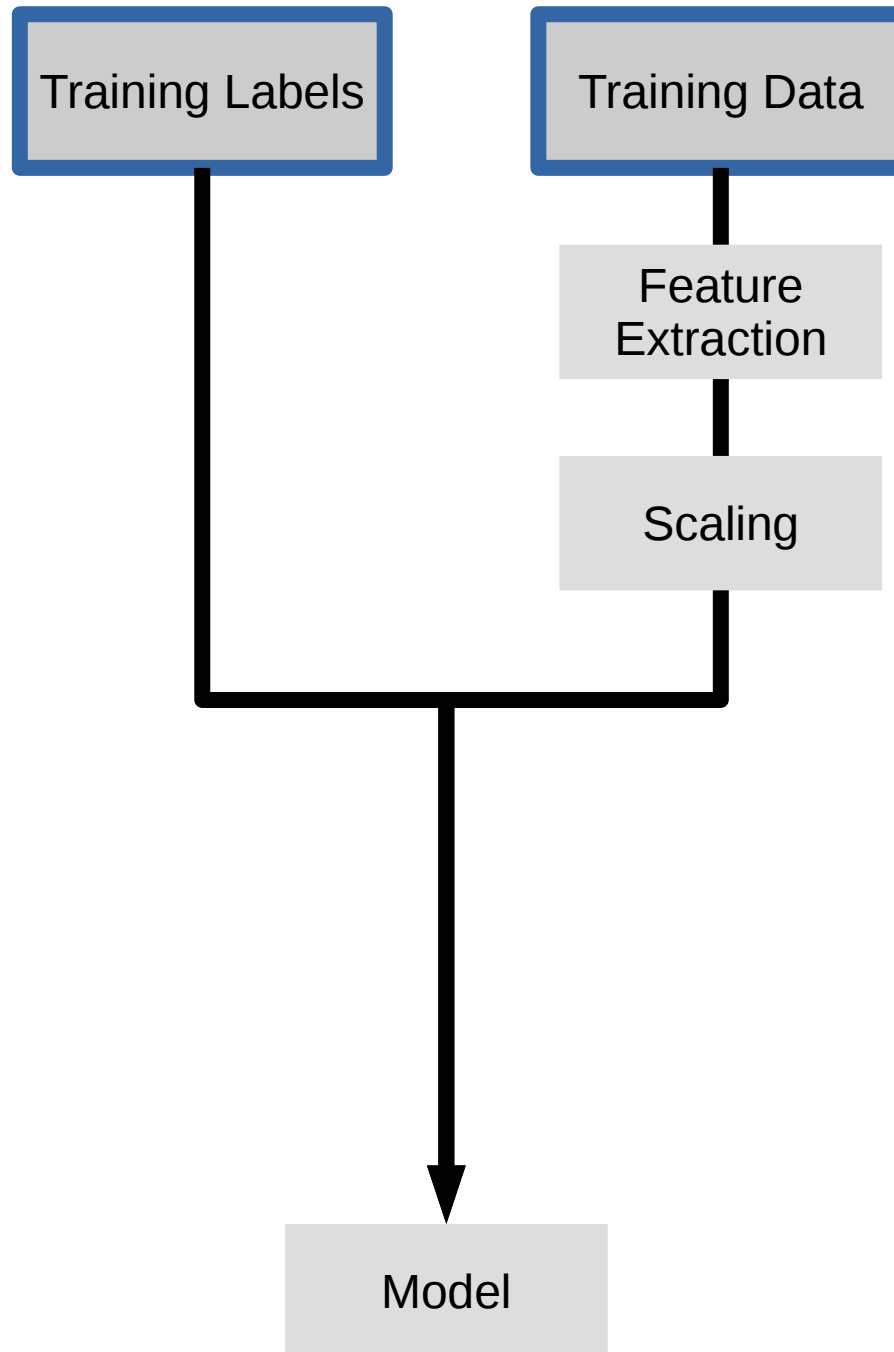
X_train, X_test, y_train, y_test = train_test_split(X, y)

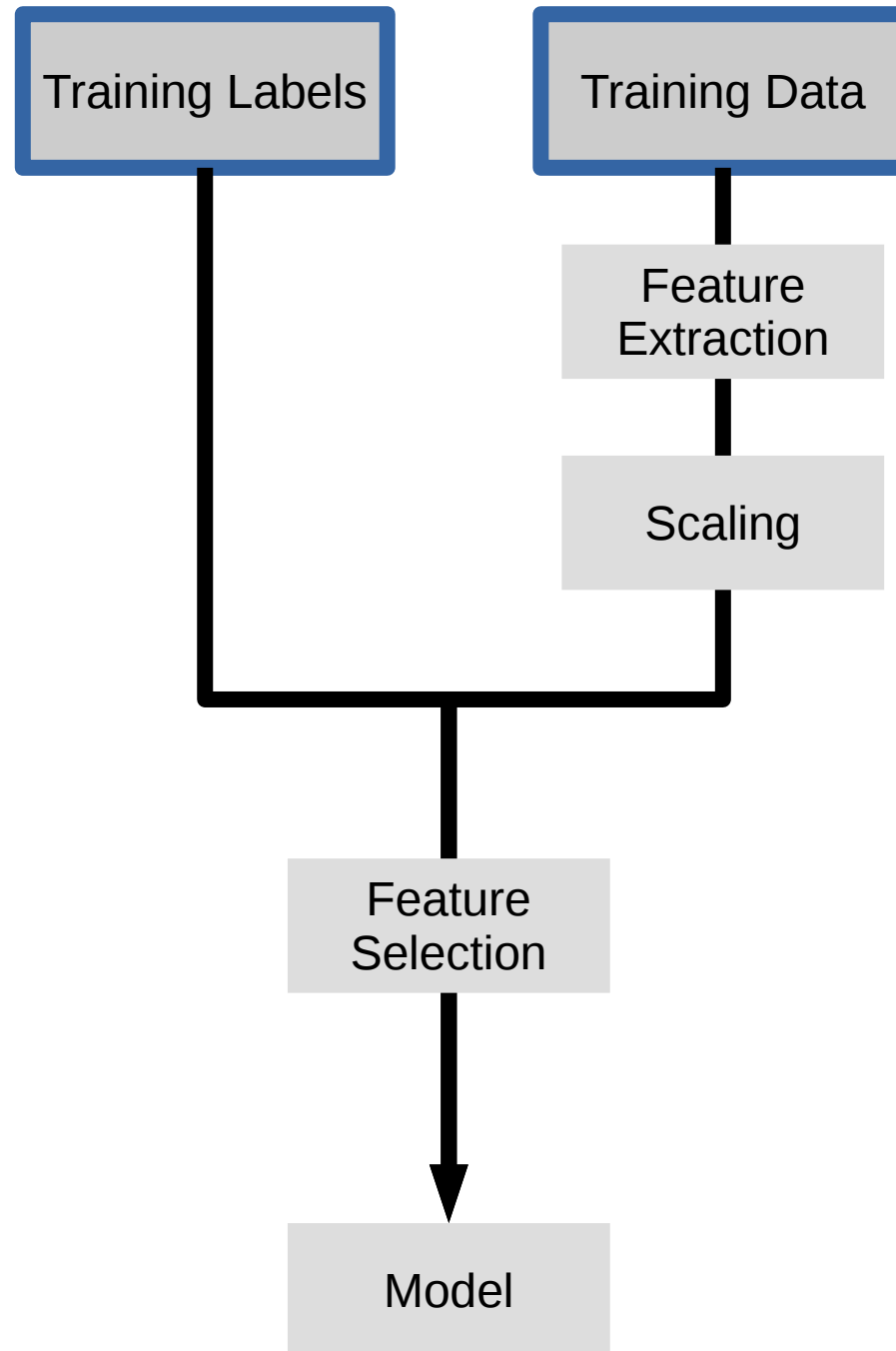
param_grid = {'C': 10. ** np.arange(-3, 3),
               'gamma': 10. ** np.arange(-3, 3)}
grid = GridSearchCV(SVC(), param_grid=param_grid)
grid.fit(X_train, y_train)
grid.predict(X_test)
grid.score(X_test, y_test)
```



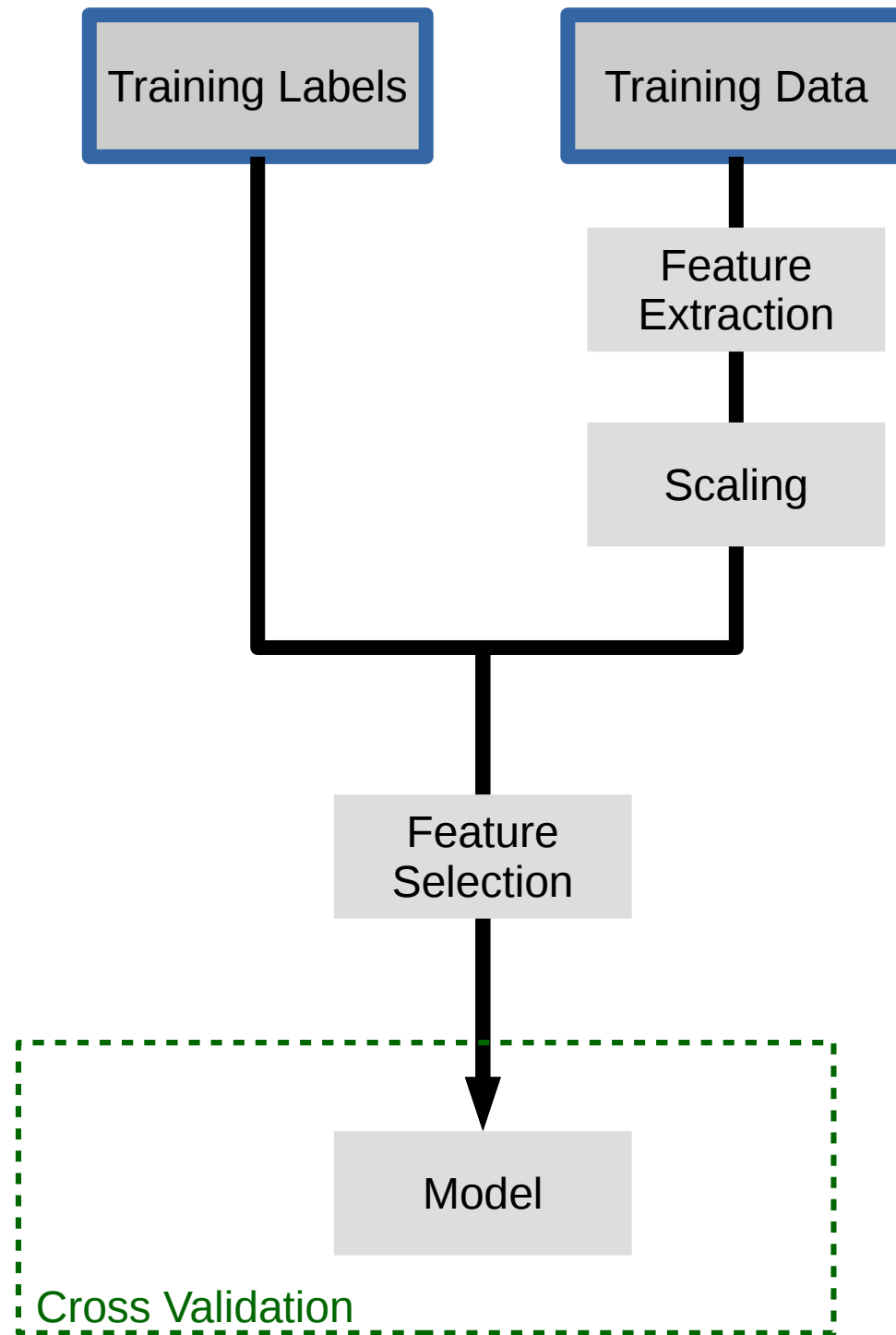


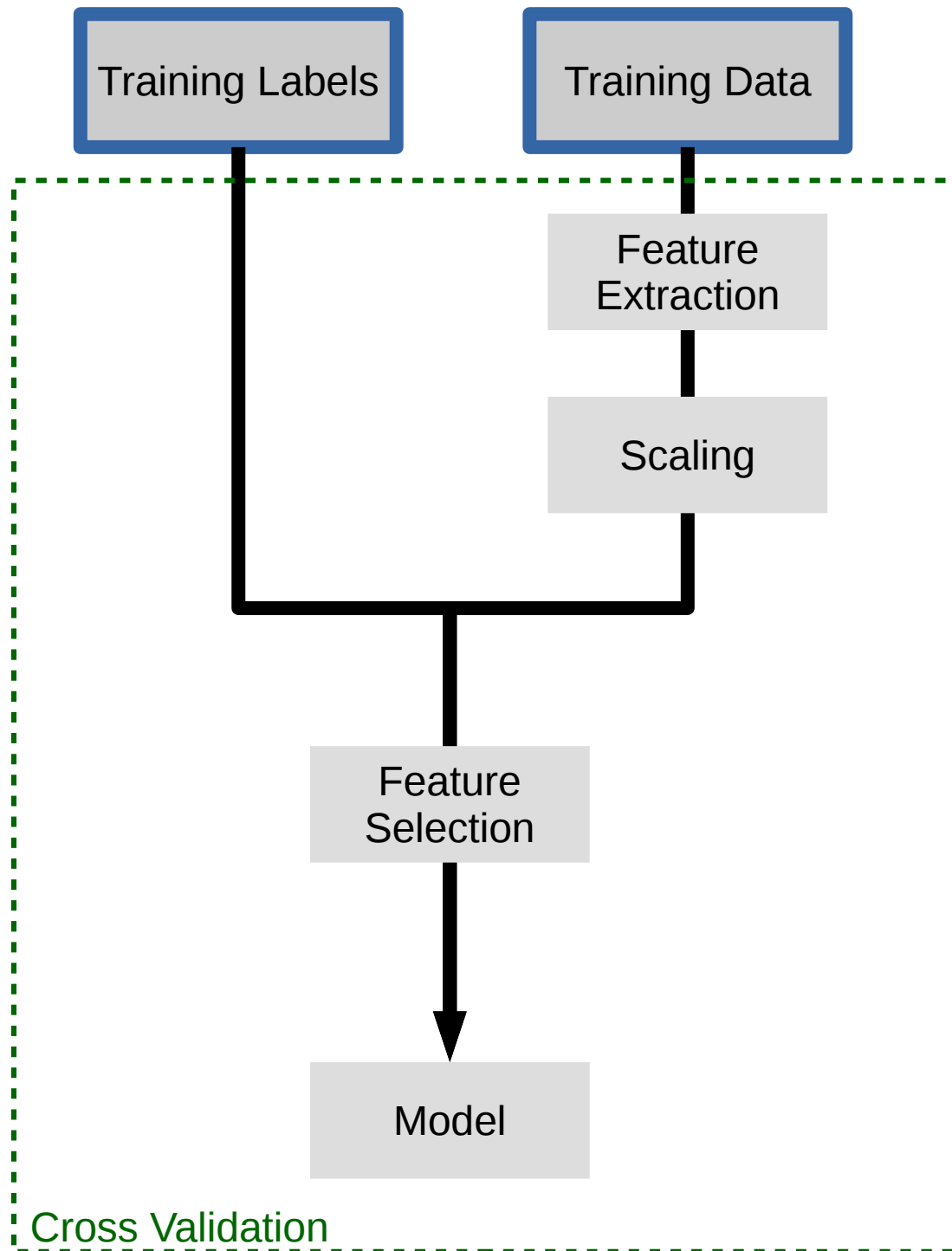










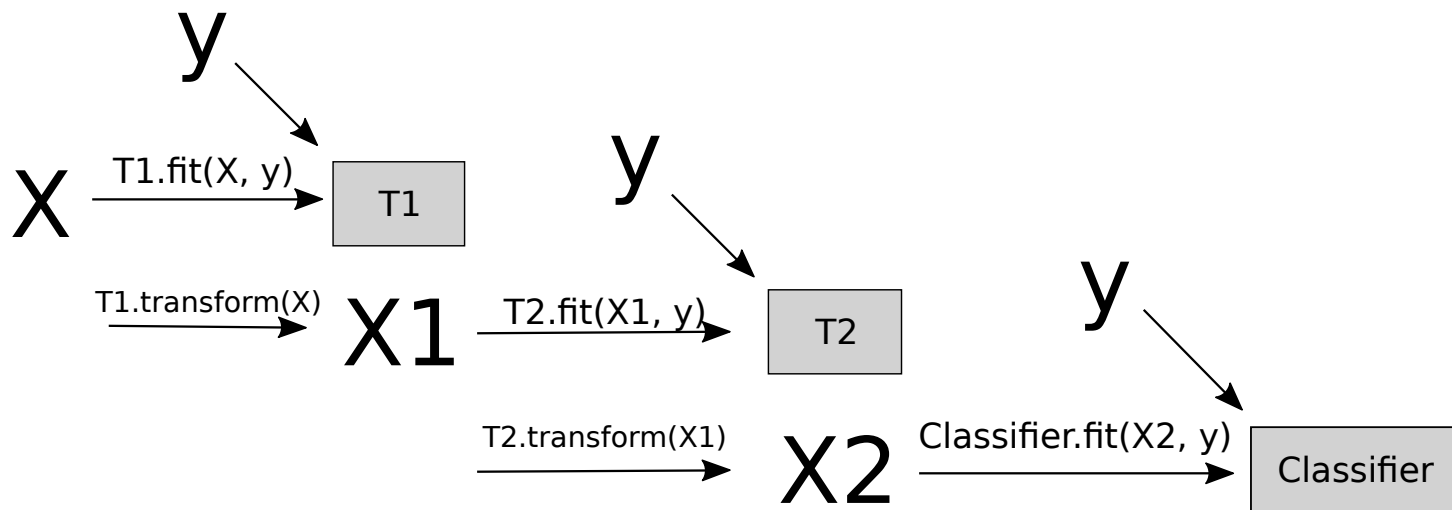


# Pipelines

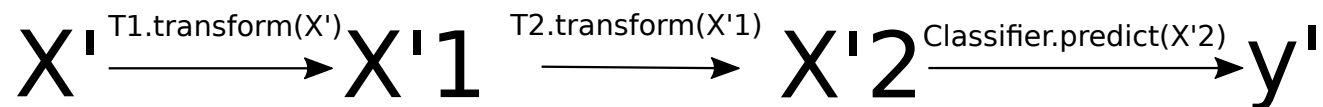
```
pipe = make_pipeline(T1(), T2(), Classifier())
```



`pipe.fit(X, y)`



`pipe.predict(X')`



# Combining Pipelines and Grid Search

```
param_grid = {'svc__C': 10. ** np.arange(-3, 3),  
              'svc__gamma': 10. ** np.arange(-3, 3)}  
  
scaler_pipe = make_pipeline(StandardScaler(), SVC())  
grid = GridSearchCV(scaler_pipe, param_grid=param_grid, cv=5)  
grid.fit(X_train, y_train)
```

# Combining Pipelines and Grid Search II

Searching over parameters of the preprocessing step

```
param_grid = {'selectkbest__k': [1, 2, 3, 4],  
              'svc__C': 10. ** np.arange(-3, 3),  
              'svc__gamma': 10. ** np.arange(-3, 3)}  
  
scaler_pipe = make_pipeline(SelectKBest(), SVC())  
grid = GridSearchCV(scaler_pipe, param_grid=param_grid, cv=5)  
grid.fit(X_train, y_train)
```

Do cross-validation over all steps jointly.  
Keep a separate test set until the very end.

## Sample application: Sentiment Analysis

# IMDB Movie Reviews Data

## **Review:**

One of the worst movies I've ever rented. Sorry it had one of my favorite actors on it (Travolta) in a nonsense role. In fact, anything made sense in this movie.

Who can say there was true love between Eddy and Maureen?  
Don't you remember the beginning of the movie ?

Is she so lovely? Ask her daughters. I don't think so.

**Label:** negative

**Training data:** 12500 positive, 12500 negative



# Bag Of Word Representations

`CountVectorizer / TfidfVectorizer`

# Bag Of Word Representations

`CountVectorizer / TfidfVectorizer`

`"This is how you get ants."`

# Bag Of Word Representations

CountVectorizer / TfidfVectorizer

"This is how you get ants."

tokenizer

↓  
['this', 'is', 'how', 'you', 'get', 'ants']

# Bag Of Word Representations

CountVectorizer / TfidfVectorizer

"This is how you get ants."

tokenizer

↓  
['this', 'is', 'how', 'you', 'get', 'ants']

↓  
Build a vocabulary over all documents

↓  
['aardvak', 'amsterdam', 'ants', ... 'you', 'your', 'zyxst']

# Bag Of Word Representations

CountVectorizer / TfidfVectorizer

"This is how you get ants."

tokenizer

['this', 'is', 'how', 'you', 'get', 'ants']

Build a vocabulary over all documents

['aardvak', 'amsterdam', 'ants', ... 'you', 'your', 'zyxst']

Sparse matrix encoding

aardvak	ants	get	you	zyxst
[0, ..., 0, 1, 0, ... , 0, 1 , 0, ..., 0, 1, 0, .....	0]			

# N-grams (unigrams and bigrams)

`CountVectorizer` / `TfidfVectorizer`

# N-grams (unigrams and bigrams)

`CountVectorizer / TfidfVectorizer`

`"This is how you get ants."`

# N-grams (unigrams and bigrams)

`CountVectorizer` / `TfidfVectorizer`

"This is how you get ants."

Unigram tokenizer



`['this', 'is', 'how', 'you', 'get', 'ants']`



# N-grams (unigrams and bigrams)

CountVectorizer / TfidfVectorizer

"This is how you get ants."

Unigram tokenizer

↓  
['this', 'is', 'how', 'you', 'get', 'ants']

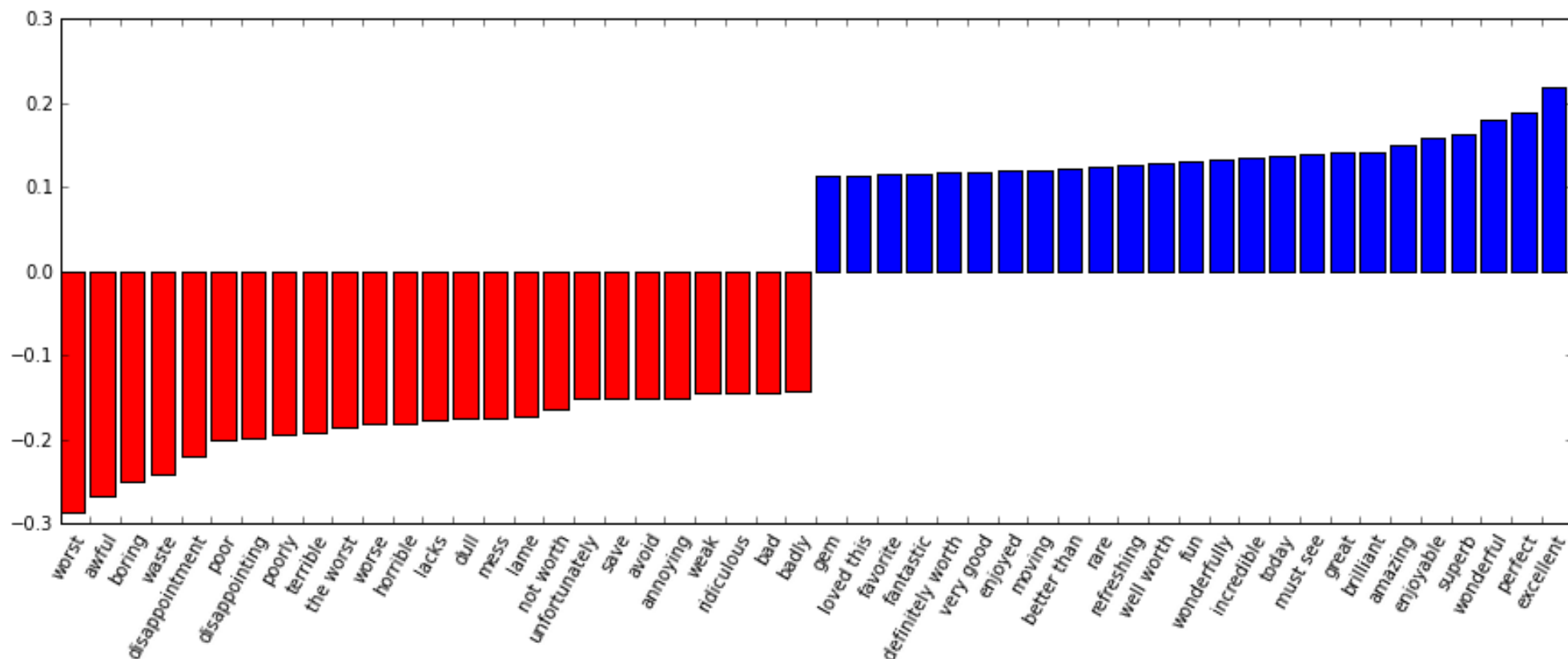
"This is how you get ants."

Bigram tokenizer

↓  
['this is', 'is how', 'how you', 'you get', 'get ants']

```
text_pipe = make_pipeline(CountVectorizer(), LinearSVC())  
text_pipe.fit(text_train, y_train)  
text_pipe.score(text_test, y_test)|
```

```
text_pipe = make_pipeline(CountVectorizer(), LinearSVC())
text_pipe.fit(text_train, y_train)
text_pipe.score(text_test, y_test)
```



# Scaling Up

# Three regimes of data

- Fits in RAM
- Fits on a Hard Drive
- Doesn't fit on a single PC

# Three regimes of data

- Fits in RAM (up to 256 GB?)
- Fits on a Hard Drive (up to 6TB?)
- Doesn't fit on a single PC

# Nobody ever got fired for using Hadoop on a cluster

Antony Rowstron, Dushyanth Narayanan, Austin Donnelly, Greg O'Shea, and Andrew Douglas

10 April 2012

"256Gb ought to be enough for anybody."  
- me

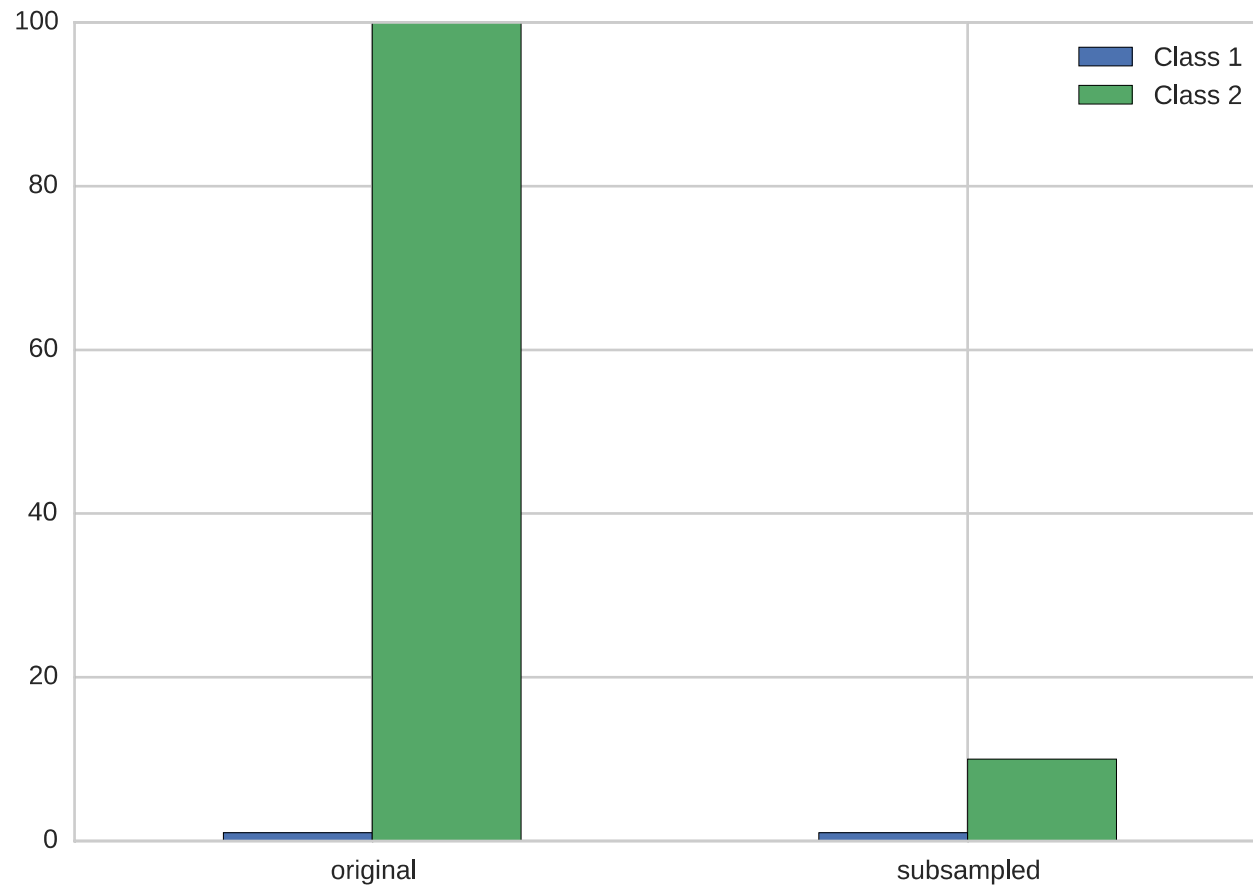


"256Gb ought to be enough for anybody."  
- me

(for machine learning)

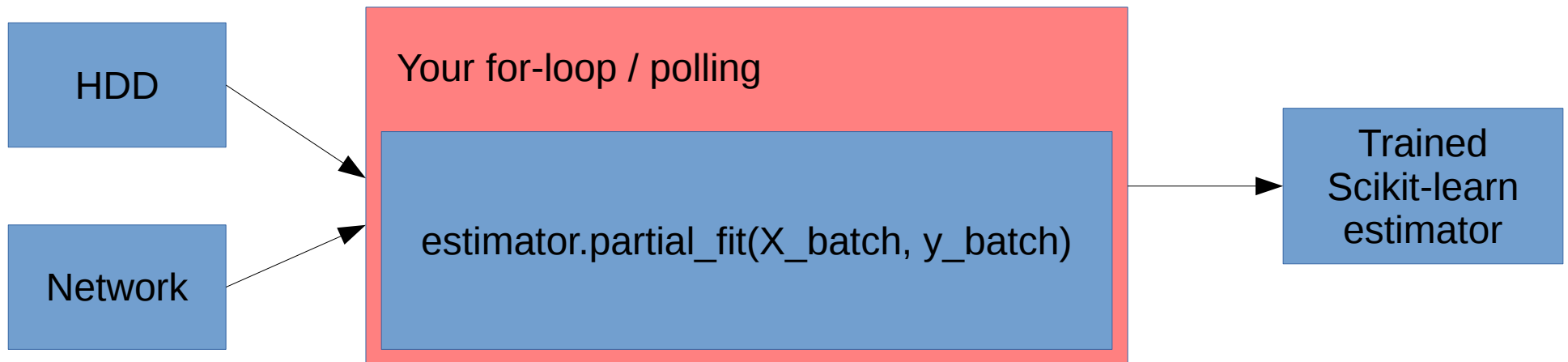
# Subsample!

# Subsample!



Out of core: The scikit-learn way

# The Partial Fit Interface



# Supported Algorithms

- `SGDClassifier/Regressor`, `Perceptron`
- `Naive Bayes`
- `MinibatchKMeans`
- `Birch`
- `IncrementalPCA`
- `MiniBatchDictionaryLearning`
- `Scalers`
- `Latent Dirichlet Allocation`
- `Stateless transformations`

# Hashing Trick

HashingVectorizer

"This is how you get ants."

tokenizer

['this', 'is', 'how', 'you', 'get', 'ants']

hashing

[hash('this'), hash('is'), hash('how'), hash('you'),  
hash('get'), hash('ants')]  
= [832412, 223788, 366226, 81185, 835749, 173092]

Sparse matrix encoding

[0, ..., 0, 1, 0, ..., 0, 1, 0, ..., 0, 1, 0, ..., 0]

# Text Classification: Hashing Trick

```
sgd = SGDClassifier()
hashing_vectorizer = HashingVectorizer()

for batch_name in glob("*.pickle"):
    with open(batch_name) as f:
        text_batch, y_batch = pickle.load(batch_name)

    X_batch = hashing_vectorizer.transform(text_batch)
    sgd.partial_fit(X_batch, y_batch, classes=[0, 1])
```



# What's new?


## **0.17 (stable)**

- Latent Dirichlet Allocation
- Faster NMF
- Faster T-SNE
- FunctionTransformer
- VotingClassifier

## **0.18 (development)**

- Neural Network
- Gaussian Process rewrite
- Faster PCA

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scikit-learn **version**  
**0.18.dev0** — [Other](#)  
[versions](#)

If you use the software,  
please consider [citing](#)  
[scikit-learn](#).

**3.2.4.3.1.**  
**`sklearn.ensemble.RandomForestClassifier`**  
**lassifier**  
3.2.4.3.1.1. Examples using  
`sklearn.ensemble.RandomForestClassifier`

## 3.2.4.3.1. `sklearn.ensemble.RandomForestClassifier`

```
class sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0, warm_start=False, class_weight=None)
```

[\[source\]](#)

A random forest classifier.

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement if `bootstrap=True` (default).

Read more in the [User Guide](#).

**Parameters:** **n\_estimators** : integer, optional (default=10)  
  
The number of trees in the forest.  
  
**criterion** : string, optional (default="gini")  
  
The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain. Note: this parameter is tree-specific.  
  
**max\_features** : int, float, string or None, optional (default="auto")

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This documentation is for  
scikit-learn **version**  
**0.18.dev0** — [Other](#)  
[versions](#)

If you use the software,  
please consider [citing](#)  
[scikit-learn](#).

**3.2.4.3.1.**  
**sklearn.ensemble.RandomForestC**  
**lassifier**  
3.2.4.3.1.1. Examples using  
sklearn.ensemble.RandomForestClas  
sifier

## 3.2.4.3.1. sklearn.ensemble.RandomForestClassifier

```
class sklearn.ensemble.RandomForestClassifier(n_estimators=10, criterion='gini', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0, warm_start=False, class_weight=None)
```

[\[source\]](#)

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**max\_features** : int, float, string or None, optional (default="auto")

# Engineering Scikit-Learn

Goal:

High quality, easy to use machine learning library.

Goal:

High quality, easy to use machine learning library.  
Keep it usable, keep it maintainable.

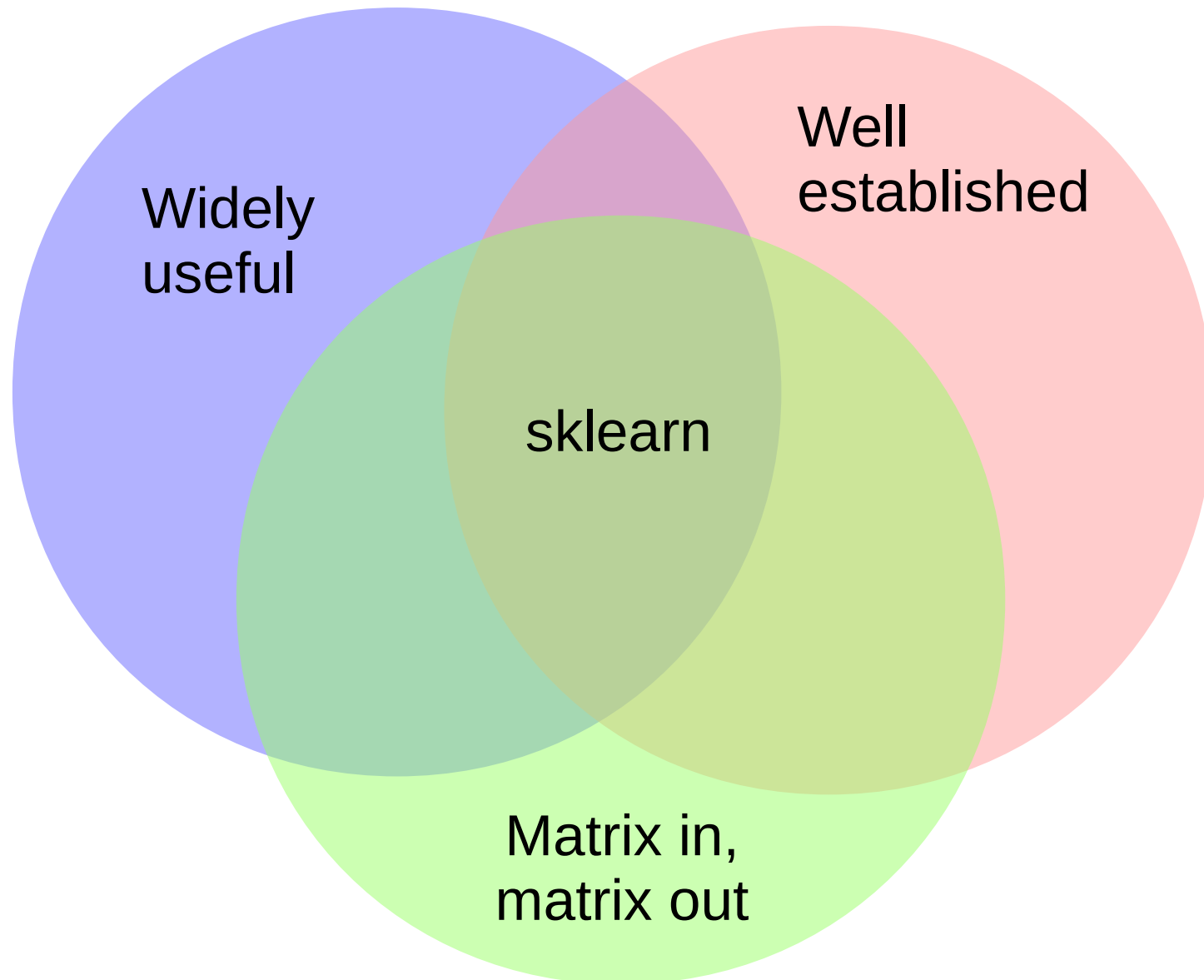
Simple things should be simple, complex things  
should be possible.

Alan Kay

# Methods



# Scoping



# Simplicity

```
est = Est()  
est.fit(X_train, y_train)  
est.score(X_test, y_test)
```

# Consistency

```
grid = GridSearchCV(svm,param_grid)
grid.fit(X_train, y_train)
grid.score(X_test, y_test)
```

# Sensible Defaults

Everything is default constructible!

```
for clf in [KneighborsClassifier(),
            SVC(),
            DecisionTreeClassifier(),
            RandomForestClassifier(),
            AdaBoostClassifier(),
            GaussianNB(),
            LDA(),
            QDA()]:
    clf.fit(X_train, y_train)
    print(clf.score(X_test, y_test))
```

# Common Tests

```
classifiers = all_estimators(type_filter='classifier')
for name, Classifier in classifiers:
    # test classifiers can handle non-array data
    yield check_classifier_data_not_an_array, name, Classifier
    # test classifiers trained on a single label
    # always return this label
    yield check_classifiers_one_label, name, Classifier
    yield check_classifiers_classes, name, Classifier
    yield check_classifiers_pickle, name, Classifier
    yield check_estimators_partial_fit_n_features, name, Classifier
```

# Flat Class Hierarchy, Few Types

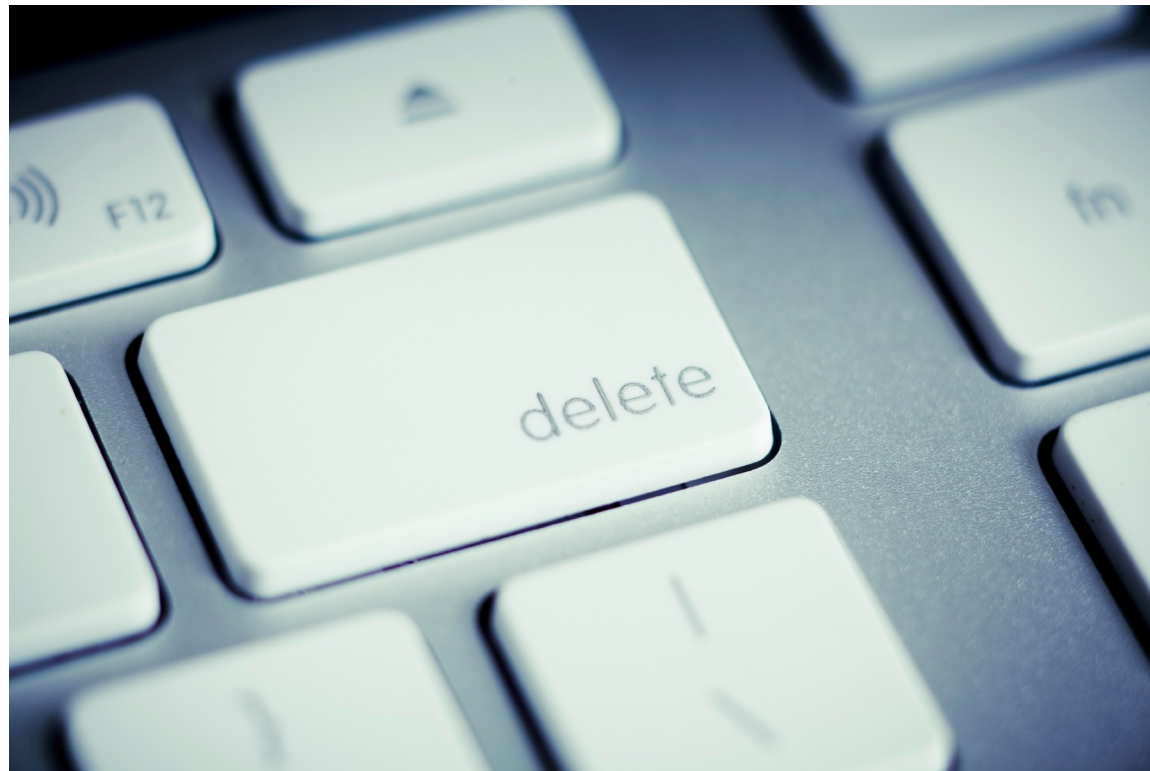
- Numpy arrays / sparse matrices
- Estimators
- [Cross-validation objects]
- [Scorers]

# No Framework

“This looks frameworkish.” means “try again.”

# Avoid Code

- Code rots!
- Hail all code deleters!





# Three-Way Documentation

## 1.9. Ensemble methods

The goal of **ensemble methods** is to combine the predictions of several base estimators built with a given learning algorithm in order to improve generalizability / robustness over a single estimator.

Two families of ensemble methods are usually distinguished:

- In **averaging methods**, the driving principle is to build several estimators independently and then to average their predictions. On average, the combined estimator is usually better than any of the single base estimator because its variance is reduced.

**Examples:** *Bagging methods, Forests of randomized trees, ...*

- By contrast, in **boosting methods**, base estimators are built sequentially and one tries to reduce the bias of the combined estimator. The motivation is to combine several weak models to produce a powerful ensemble.

**Examples:** *AdaBoost, Gradient Tree Boosting, ...*

## `sklearn.ensemble.RandomForestClassifier`

```
class sklearn.ensemble. RandomForestClassifier(n_estimators=10, criterion='gini',
max_depth=None, min_samples_split=2, min_samples_leaf=1,
min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None,
bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0,
warm_start=False)
```

[\[source\]](#)

A random forest classifier.

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting.

**Parameters:** `n_estimators` : integer, optional (default=10)

The number of trees in the forest.

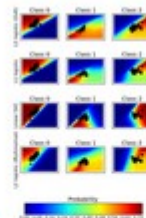
`criterion` : string, optional (default="gini")

The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain. Note: this parameter is tree-specific.

## Examples



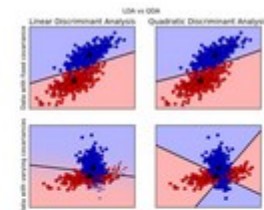
*Recognizing  
hand-written digits*



*Plot classification  
probability*



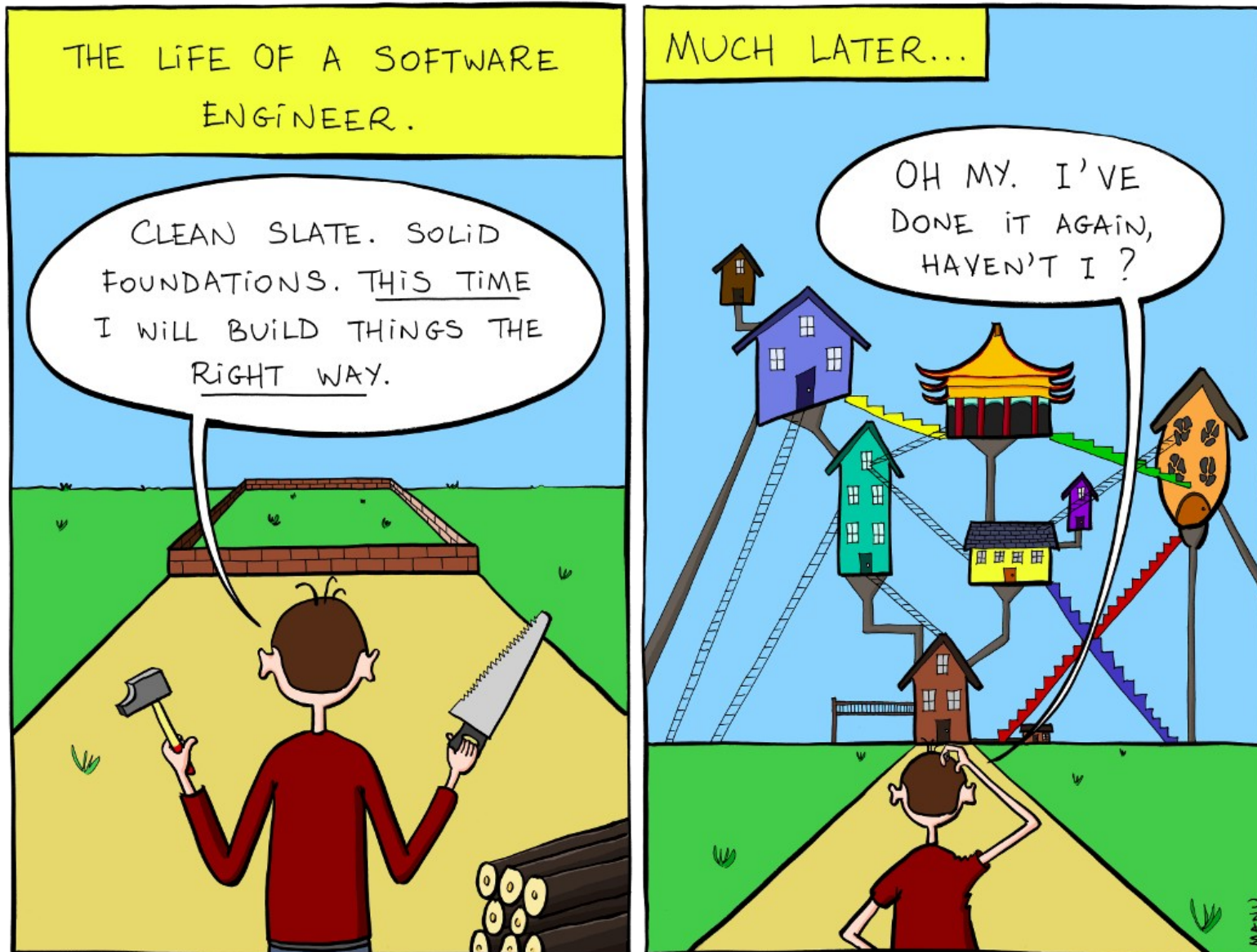
*Classifier comparison*



*Linear and Quadratic  
Discriminant Analysis  
with confidence  
ellipsoid*

# Challenges

# Feature Creep



# Two Language Problem



# Backward compatibility

```
from sklearn.cross_validation import Bootstrap  
Bootstrap(10)
```

```
sklearn/cross_validation.py:685:
```

```
DeprecationWarning: Bootstrap will no longer  
be supported as a cross-validation method as of  
version 0.15 and will be removed in 0.17.
```

# Backward compatibility

```
>>> import pickle
>>> s = pickle.dumps(clf)
>>> clf2 = pickle.loads(s)
>>> clf2.predict(X[0])
array([0])
>>> y[0]
0
```

# Correctness Testing



# Project Size

🔗 193 Open ✓ 2,083 Closed

ⓘ 337 Open ✓ 1,318 Closed

In a Nutshell, scikit learn...

... has had 17,356 commits made by 424 contributors  
representing 433,767 lines of code



# Developer churn

- Two Full time devs (Oliver Grisel & Myself)
- Hundreds of “drive by” contributors

# Video Series

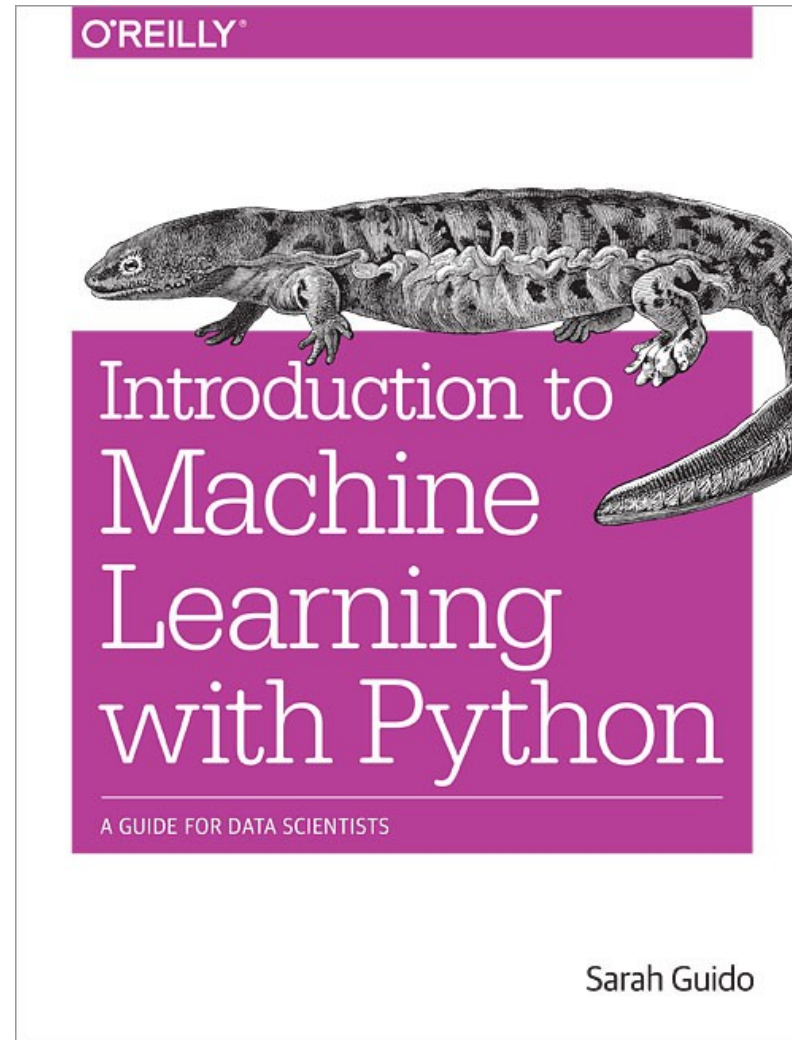
## Advanced Machine Learning with scikit-learn

50% Off Coupon Code: AUTHD

# Video Series

## Advanced Machine Learning with scikit-learn

50% Off Coupon Code: AUTHD



# Thank you for your attention.



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